Application of Neural Network Compensation Algorithm in MEMS-based Attitude Detection (Postprint)

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Date: 2018-06-19T00:00:00+00:00

Abstract

To address the issue of attitude measurement errors in MEMS sensor-based attitude detection and to further enhance attitude estimation accuracy, a neural network-based attitude estimation error compensation method is proposed. By utilizing a dataset collected from actual flight experiments conducted with an open-source micro aerial vehicle in an indoor environment, and harnessing the nonlinear mapping capabilities of BP neural networks, an attitude error compensation model relating MEMS sensor outputs to attitude estimation errors is constructed. Based on the output information from MEMS sensors, error compensation angles for roll, pitch, and yaw are directly predicted. Experimental results demonstrate that the proposed neural network-based attitude compensation approach significantly reduces attitude estimation errors, thereby confirming the effectiveness of neural networks in improving attitude detection accuracy.

Full Text

Preamble

Title: Application of Neural Network Compensation Algorithm in MEMS-Based Attitude Detection

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Abstract: Aiming at the attitude measurement errors prevalent in attitude detection fields based on micro-electro-mechanical sensors, this paper proposes a neural-network-based approach for attitude estimation error compensation. Utilizing publicly available datasets from real indoor flight experiments conducted with a micro-air vehicle, this work establishes an attitude error compensation model that maps MEMS sensor outputs to attitude estimation errors by leveraging the nonlinear mapping capabilities of BP neural networks. The model directly predicts compensation values for roll, pitch, and yaw angles based on MEMS sensor output information. Experimental results demonstrate that the proposed neural network compensation method significantly reduces attitude estimation errors, confirming that neural networks can effectively improve attitude detection accuracy.

Keywords: neural network; attitude compensation; micro-electro-mechanical sensors; attitude measurement

0 Introduction

Micro-electro-mechanical systems (MEMS) are considered the core technology of the Internet of Things (IoT). Compared with conventional sensors, MEMS sensors offer advantages including small size, high precision, high integration density, and low cost, making them widely applicable in attitude detection [1–3] and indoor positioning [4–6]. However, due to manufacturing imperfections such as scale factor deviations and sensor axis misalignments, as well as external factors like temperature and noise, the actual output of MEMS sensors deviates from ideal values. Consequently, results obtained from attitude detection or indoor positioning studies based on these sensor outputs exhibit substantially increased errors compared to expected values.

The conventional approach for attitude measurement using MEMS sensors involves sensor calibration followed by multi-sensor data fusion to obtain final attitude estimates. Nevertheless, both sensor calibration accuracy and data fusion algorithm performance affect the ultimate measurement results, and traditional attitude detection methods cannot compensate for errors between detected and true attitudes.

Two primary methods exist for obtaining more accurate measurement results. The first approach improves sensor calibration precision to enhance output reliability. Common calibration methods include turntable calibration [7], six-position twenty-four-point calibration [8], and twenty-six-position calibration [9]. Turntable-based methods require expensive, bulky equipment and demand high-precision control of rotation angles during calibration, limiting their use to laboratory environments. While six-position and twenty-six-position methods avoid costly precision equipment, the six-position approach struggles to ensure orthogonality among the four points at each position, and the computational complexity of the twenty-six-position method renders it impractical for real-world applications.

The second approach involves identifying appropriate data fusion algorithms. Kalman filter (KF) [10] and its derivatives, including extended Kalman filter (EKF) [11] and unscented Kalman filter (UKF) [12], are widely employed for multi-sensor data fusion. These methods can provide reasonably accurate attitude outputs when MEMS sensor results are sufficiently reliable. However, KF only applies to linear motion analysis; EKF fails to track target attitudes effectively under strong nonlinear motion; and UKF' s substantial computational load consumes significant embedded system resources, reducing capacity for other control tasks. When sensor outputs exhibit poor reliability or high noise levels, the gap between obtained attitude results and actual values increases dramatically.

Therefore, with sensor calibration and multi-sensor data fusion methods established, developing appropriate techniques to further improve MEMS-based attitude detection accuracy holds significant research value. Addressing these challenges, this paper proposes a neural-network-based attitude compensation method to correct errors between final attitude detection results and actual values caused by sensor calibration inaccuracies and data fusion limitations, thereby enhancing MEMS-based attitude detection precision. This approach uses MEMS sensor outputs as inputs and leverages neural networks' nonlinear mapping capabilities to obtain error compensation values for Euler angles (roll, pitch, and yaw) output by MEMS attitude detection systems. Experimental results demonstrate that neural network compensation yields MEMS-based attitude estimates that more closely approximate true attitudes.

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1 Overall Method Description

The conventional MEMS-based attitude detection workflow, illustrated by the dashed line in Figure 1 [Figure 1: see original paper], operates unidirectionally, allowing errors to propagate through each stage. Errors from MEMS sensor calibration affect multi-sensor data fusion algorithm performance, amplifying data fusion errors, yet traditional measurement methods cannot compensate for errors accumulated during the MEMS detection process.

This paper focuses on utilizing neural networks' strong nonlinear mapping capabilities to compensate for errors in the attitude measurement process, given fixed MEMS sensor calibration and selected data fusion methods. The overall structure of the proposed neural-network-based attitude compensation method is shown in Figure 1 [Figure 1: see original paper], comprising attitude measurement and attitude compensation components. The attitude measurement section includes measurement sensors (three-axis gyroscope, three-axis accelerometer, and three-axis magnetometer), sensor calibration, and multi-sensor data fusion algorithms. In the diagram, G , A , M represent pre-calibration outputs from the three sensor types, while , , denote the roll, pitch, and yaw angles output by the data fusion algorithm.

The attitude compensation component consists of a compensation neural network. The compensated attitude angles are , , , respectively. To improve MEMS detection system accuracy for practical applications, attitude detection errors must first be obtained using a specific reference system, with reference system outputs denoted as _f, _f, _f. Common reference systems include optical capture systems (e.g., Vicon by Oxford Metrics Limited), laser tracker systems (e.g., FARO laser trackers from the US, Leica from Germany), and infrared camera array systems (e.g., NDI from Canada).

The compensation neural network is trained using MEMS detection system sensor outputs and attitude error estimates obtained by comparing the reference system with the MEMS measurement system. Processed MEMS sensor outputs serve as neural network inputs, while the network outputs represent MEMS system attitude measurement error compensation values. The final MEMS system attitude measurement results are obtained after compensation through the neural network.

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2 Attitude Compensation Neural Network Design

The compensation neural network implementation process, shown in Figure 2 [Figure 2: see original paper], includes network construction, training, and prediction.

2.1 Network Construction

A BP neural network is a feedforward neural network comprising an input layer, hidden layer(s), and output layer. Hecht-Nielsen has proven that a feedforward neural network with a single hidden layer can approximate any function with multiple variables [13]. Therefore, this paper designs a three-layer BP neural network with one hidden layer to predict attitude detection errors, as illustrated in Figure 3 [Figure 3: see original paper].

As previously discussed, MEMS attitude detection system output errors primarily originate from sensor calibration errors and data fusion algorithms. With the data fusion algorithm fixed, sensor output data reliability directly determines attitude detection system accuracy. Consequently, the designed neural network uses three-axis angular velocity, three-axis acceleration, and three-axis magnetic field information from MEMS sensor outputs as inputs, with m = 9 input layer neurons. The output layer consists of n = 3 neurons representing roll, pitch, and yaw error compensation values. The number of hidden layer neurons can be determined using empirical formula (1), where a is an integer in the range [1, 10]. Through extensive experimentation, this paper selects l = 11 hidden layer neurons.

The hidden layer activation function is:

$$f_1(x) = \frac{1 - e^{-x}}{1 + e^{-x}}$$

where a__j represents hidden layer thresholds, and l__j represents the input to hidden layer node j, determined by input layer inputs and weights between input and hidden layers:

$$l_j = \sum_{i=1}^{9} w_{ij} x_i$$

The output layer activation function is:

$$f_2(x) = x$$

used to output network predictions. Here, b__k represents output layer thresholds, and n__k represents the input to output layer node k, determined by hidden layer neuron outputs and weights between hidden and output layers:

$$n_k = \sum_{j=1}^{11} w_{jk} f_1(l_j)$$

The overall training error is defined as:

$$E = \frac{1}{2} \sum_{k=1}^{3} (y_k - o_k)^2$$

where y__k represents network output values and o__k represents desired output values.

This paper employs gradient descent to update neural network weights and thresholds. Updated output layer weights and thresholds are:

$$w_{jk}^{(p+1)} = w_{jk}^{(p)} - \eta \frac{\partial E}{\partial w_{jk}^{(p)}}$$

$$b_k^{(p+1)} = b_k^{(p)} - \eta \frac{\partial E}{\partial b_k^{(p)}}$$

Updated hidden layer weights and thresholds are:

$$w_{ij}^{(p+1)} = w_{ij}^{(p)} - \eta \frac{\partial E}{\partial w_{ij}^{(p)}}$$

$$a_j^{(p+1)} = a_j^{(p)} - \eta \frac{\partial E}{\partial a_j^{(p)}}$$

where p represents update iterations and   represents the learning rate.

2.2 Training Samples

This paper utilizes an open-source micro air vehicle (MAV) dataset from real flight experiments conducted in a 10m×10m×10m indoor environment equipped with a Vicon motion capture system [14]. The dataset comprises three sub-datasets: "1LoopDown," "2LoopDown," and "3LoopDown," corresponding to three MAV flight experiments with progressively increasing flight durations and sample counts. All three datasets contain data from both MEMS and Vicon systems. Vicon system data includes spatial position, attitude, and angular velocity information captured by the ground-based Vicon system. MEMS system data includes three-axis acceleration, three-axis angular velocity, three-axis magnetic field information captured by onboard MEMS sensors, and attitude information output by the embedded AscTec data fusion algorithm in the MAV' s processor. Both systems represent MAV attitude using Euler angles. The 1LoopDown dataset contains 6,401 samples, 2LoopDown contains 16,795 samples, and 3LoopDown contains 24,033 samples.

This paper uses Vicon-captured MAV attitude as ground truth reference to obtain error values between AscTec data fusion algorithm outputs and reference system captures. These attitude error values serve as training samples y = [e e e] , where e , e , e represent roll, pitch, and yaw errors, respectively. Sensor output information from the dataset serves as neural network input training samples x = [g g_y g_z a a_y a_z m m_y m_z] , where g , g_y, g_z represent three-axis angular velocity; a , a_y, a_z represent three-axis acceleration; and m , m_y, m_z represent three-axis magnetic field information.

To train a more reliable neural network following the principle of large training samples, this paper uses the "3LoopDown" dataset for network training to establish an attitude error compensation model mapping MEMS sensor outputs to attitude estimation errors. The "1LoopDown" dataset is used for prediction to evaluate the designed neural network' s performance in improving MEMS-based attitude detection accuracy.

2.3 Network Training

Before neural network training, input and output samples are normalized using equations (2) and (3) to map all samples into the range [-1, 1]:

$$x_i' = 2\frac{x_i - x_{\min}}{x_{\max} - x_{\min}} - 1$$

$$y'_j = 2\frac{y_j - y_{\min}}{y_{\max} - y_{\min}} - 1$$

where x_i' and y_j' represent the i-th and j-th normalized parameters; x_i and y_j represent unnormalized parameters; x_min and y_min represent minimum values; and x_max and y_max represent maximum values of unnormalized input and output samples.

Due to the strong nonlinear relationship between compensation neural network output attitude angle errors and input sensor information, neural network weight initializations—including input-to-hidden layer weights w_ij and hidden-to-output layer weights w_jk—are randomly set within [-1, 1], where i [1, 9], j [1, 11], k [1, 3].

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3 Neural Network Attitude Compensation Results and Analysis

To evaluate the proposed neural network' s performance in attitude error compensation, experiments are conducted using the "1LoopDown" dataset. The designed compensation neural network is applied to compensate for errors in attitude information measured by the MAV' s onboard MEMS system.

For further comparison of compensation neural network performance in improving MEMS attitude detection accuracy, two additional comparative experiments are established. Since sensor calibration is completed in these MAV flight experiments, besides the AscTec data fusion algorithm embedded in the MAV processor, this paper also compares two widely-used attitude detection data fusion methods: Madgwick' s gradient descent method [15] and Mahony' s complementary filter method [16].

Figure 4 [Figure 4: see original paper] displays the pitch, roll, and yaw angles measured by four methods using the MEMS system. The results show that before neural network compensation, MAV attitude information output by the MEMS system deviates significantly from reference system outputs. Similarly, widely-used Madgwick and Mahony algorithms also exhibit noticeable gaps between their MAV attitude estimates and reference system captures, though their overall detection performance surpasses that of the AscTec data fusion method embedded in the MAV processor. After compensation using the proposed neural network, the detection results from all three methods more closely approximate the ground reference system. Since neural network predictions inherently contain errors, some noise appears in the compensated attitude curves, which could be removed through mean filtering or fast Fourier transform methods. As this paper focuses on neural network performance for attitude error compensation, noise removal is not elaborated further.

Figure 5 [Figure 5: see original paper] illustrates attitude detection errors between the four methods and the reference system. The results demonstrate that compared with the other three methods, the MAV' s embedded data fusion algorithm' s attitude angle errors are substantially reduced after compensation, essentially achieving near-zero fluctuations.

To verify the compatibility of the designed compensation neural network with other data fusion algorithms, the neural network is applied to compensate Madgwick and Mahony algorithms. Results are shown in Figure 6 Figure 6: see original paper and (b), where black curves represent reference system-captured MAV attitude, while blue and red curves represent MAV attitude information captured by MEMS systems before and after compensation using the designed neural network, respectively.

Evidently, after compensation by the designed neural network, both methods' detection results more closely match reference system values. Therefore, the compensation neural network demonstrates good compatibility with other data fusion algorithms and can be conveniently applied to improve their attitude detection accuracy. This confirms that neural network-based attitude compensation helps further enhance MEMS system attitude detection precision.

Root mean square error (RMSE) is the most common metric for evaluating fitting performance. To more intuitively demonstrate the designed compensation neural network' s performance in improving attitude detection accuracy, Table 1 lists the RMSE values of attitude angles for three methods before and after neural network compensation.

Table 1 RMSE of Attitude Angles Before and After Compensation (Unit: Radians)

Method	Roll	Pitch	Yaw
AscTec (Before)	[value]	[value]	[value]
AscTec (After)	[value]	[value]	[value]
Madgwick (Before)	[value]	[value]	[value]
Madgwick (After)	[value]	[value]	[value]
Mahony (Before)	[value]	[value]	[value]
Mahony (After)	[value]	[value]	[value]

The table shows that after neural network compensation, attitude estimation errors from all three methods are significantly reduced, greatly improving attitude compensation precision. The designed neural network exhibits excellent compatibility with other data fusion algorithms.

4 Conclusion

To improve detection accuracy of MEMS-based attitude detection systems, this paper proposes a compensation neural network-based attitude error compensation method. The approach establishes a model mapping MEMS sensor outputs to attitude measurement errors and utilizes BP neural networks' exceptional learning capabilities to fit the strong nonlinear relationship between them. The trained neural network directly predicts required attitude error compensation information from processed MEMS sensor data. Experimental results demonstrate that neural network compensation substantially reduces MEMS system attitude detection errors and improves accuracy. Moreover, the compensation neural network shows good compatibility with other algorithms, enabling convenient application to enhance various detection methods' precision. Therefore, applying neural networks to attitude compensation proves effective for further improving MEMS system attitude detection accuracy.

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Note: Figure translations are in progress. See original paper for figures.